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Review of Significant Research on EEG based Automated Detection of Epilepsy Seizures & Brain Tumor

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Abstract— Electroencephalography (EEG) measures the electrical activity of the brain and represents a summation of post-synaptic potentials from a large number of neurons. Over a past few decades many researches all over the world, focusing and working to automate the analysis of EEG signals to identify and categorized the diseases. In this paper, we present a review of the significant researches associated with the automated detection of epileptic seizures and brain tumor using EEG signals.

Index Terms— Brain Tumor, EEG, Epilepsy Seizures, Automated, Neural Network, Wavelet Transform, Neurological diseases

1 INTRODUCTION

THE brain is one of the most complex organs of the human body, which involves billions of interacting physiological and chemical processes that give rise to experimental observed neuroelectrical activity. The signal electroencephalographic (EEG) is defined as a representation of post-synaptic potentials that are generated at cortical level by synchronous activity of about 105 (10 rates to 5) neurons. The (EEG) which provides insight information representing the brain's electrical activity is the most utilized signal to assess and detect abnormalities in the electrical activity of the brain, The EEG signal contains the useful information along with redundant or noise information.

2 EPLIEPSY SEIZURE DETECTION

Epilepsy is a common chronic neurological disorder. Epilepsy seizures are the result of the transient and unexpected electrical disturbance of the brain. About 50 million people world wide have epilepsy, and nearly two out of every three new cases are discovered in developing countries [1]. Epilepsy is more likely to occur in young children or people over the age of 65 years; however, it can occur at any time [2].

In epilepsy, the normal pattern of neuronal activity becomes disturbed, causing strange sensations, emotions, and behavior, or sometimes convulsions, muscle spasms, and loss of consciousness [1]. There are many possible causes of epilepsy. Anything that disturbs the normal pattern of neuron activity ranging from illness to brain damage to abnormal brain development can lead to seizures. Epileptic seizures are manifestations of epilepsy [3].

In the last couple of years, the EEG analysis was mostly focused on epilepsy seizure detection diagnosis. The methodology is based on three different adroit integration of computing technologies and problem solving paradigms (e.g., neural networks, wavelets, and chaos theory).

Starting with template matching algorithm (find events that match previously selected spikes), which uses a statistical approach to compare the EEG signal with a data base of known epileptic spikes [56]. This method lacks in the accuracy to detect the epilepsy.

The other methods of automatic EEG processing were based on a Fourier transform. This approach is based on earlier observations that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands. Such methods have proved beneficial for various EEG characterizations, but fast Fourier transform (FFT), suffer from large noise sensitivity. Parametric methods for power spectrum estimation such as autoregressive (AR), reduces the spectral loss problems and gives better frequency resolution. Since the EEG signals are non-stationary, the parametric methods are not suitable for frequency decomposition of these signals.

2.1 Reveiw of Neural Network based approaches

Gular et al [9] have a study the assessment of accuracy of recurrent neural networks (RNN) employing Lyapunov exponents in detection seizure in the EEG signals. Yuedong Song, Pietro Liò [20] developed an EEG epilepsy detection scheme based on the entropy based feature extraction and extreme learning machine. The proposed system employed a recently-proposed statistical parameter re-ferred to as Sample entropy (SampEn), together with extreme learning machine (ELM) which is a recently-developed classification model, to classify subjects as normal subject, patients not having an epileptic seizure or patients having an epileptic seizure. Compare the per-

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formance of ELM classifiers with a back propagation neural network (BPNN) based on a Levenberg-Marquardt back-propagation (LMBP) learning algorithm. Results show that the proposed scheme achieves an excellent performance with not only the accuracy as high as 95.67% but also with very fast learning speed (0.0250 seconds), which demonstrates its potential for real-time implementation in an epilepsy diagnosis support system.

Kezban Aslan et al. [10] have conducted a study to examine epileptic patients and perform classification of epilepsy groups. The classification process groups into partial and primary generalized epilepsy by employing Radial Basis Function Neural Network (RBFNN) and Multilayer Perceptron Neural Network (MLPNNs). The parameters acquired from the EEG signals and clinic properties of the patients are used to train the neural networks. The experimental results obtained, depicted that the predictions corresponding to the learning data sets were convincing for both neural network models. It would be stated from the results that RBFNN (total classification accuracy = 95.2%) produced better classification than MLPNN (total classification accuracy = 89.2%). From the results, it is determined that the RBFNN model can be used as a decision support tool in clinical studies to validate the epilepsy group classification after the development of the model.

M. Kemal Kiymik et al. [11] have examined the performance of the periodogram and autoregressive (AR) power spectrum methods. Owing to the automatic comparison of epileptic seizures in EEG a method is offered by them, which allows the combining of seizures that have alike overall patterns. Every channel of the EEG was first broken down into segments having comparatively stationary characteristics. For each segment the features are calculated, and all segments of all channels of the seizures of a patient are combined into clusters of same morphology. With the examination of 5 patients with scalp electrodes that demonstrated the capability of the method to cluster seizures of alike morphology and observed that ANN categorization of EEG signals with AR preprocessing gave improved outcome, and those outcome could also used for the deduction of epileptic seizure.

The use of autoregressive (AR) model is examined by Abdulhamit Subasi et al. [12] by using utmost likelihood estimation (MLE) also interpretation together with the performance of this method to dig out classifiable features from human EEG by means of Artificial Neural Networks (ANNs). It is noticed that; ANN classification of EEG signals with AR produced noteworthy results. Their approach is on the basis of the earlier where the EEG spectrum enclosed a few characteristic waveforms which fall primarily within four frequency bands-delta (< 4 Hz), theta (4–8 Hz), alpha (8–14 Hz), and beta (14–30 Hz). For the automatic classification of seizures a method is offered as well as attained a classification rate of 92.3% by means of a neural network with a single hidden unit as a classifier. The classification percentages of AR with MLE on test data are over 92%. As a result of employing FFT as preprocessing in the neural net an average of 91% classification is attained.

A wavelet-chaos-neural network methodology for classification of electroencephalograms (EEGs) into healthy, ictal, and interictal EEGs has been offered by Samanwoy Ghosh-Dastidar et al. [13]. In order to decompose the EEG into delta, theta, alpha, beta, and gamma sub-bands the wavelet analysis is utilized. Three parameters are used for EEG representation: standard deviation (quantifying the signal variance), correlation dimension, and largest Lyapunov exponent (quantifying the nonlinear chaotic dynamics of the signal). The classification accuracies of the following techniques are compared: 1) unsupervised - means clustering; 2) linear and quadratic discriminant analysis; 3) radial basis function neural network; 4) Levenberg–Marquardt back propagation neural network (LMBPNN). The research was carried out in two phases with the intention of minimizing the computing time and output analysis, band-specific analysis and mixed-band analysis. In the second phase, over 500 different combinations of mixed-band feature spaces comprising of promising parameters from phase one of the research were examined. It is decided that all the three key components the wavelet-chaos-neural network methodology are significant for enhancing the EEG classification accuracy. Judicious combinations of parameters and classifiers are required to perfectly discriminate between the three types of EEGs. The outcome of the methodology clearly let know that a specific mixed-band feature space comprising of nine parameters and LMBPNN result in the highest classification accuracy, a high value of 96.7%.

To categorize the types of epileptic seizures a simple approach is offered by Najumnissa and Shenbaga Devi [14]. Their concentration is on the detection of epileptic seizures from scalp EEG recordings. On the basis of two stages seizures are categorized: Stage I was a set of neural network-based epileptic seizure detector and stage II was a neural network, which classifies the abnormal EEG from, stage I. From 34 patients 436 features have been chosen. In order to train the neural network out of 436 feature sets, 330 feature sets from 26 patients are utilized and the remaining 106 feature sets of eight patients were kept for testing. By means of the wavelet transform technique the features are pulled out. Two networks are used by them one is for detecting normal and abnormal conditions, the second one for classification. The onset of the seizure was continuously moving by the window and the time of onset was recognized. In the tests of the system on EEG denoted a success rate of 94.3% was obtained. The system was made as a real-time detector by their method and it enhanced the clinical service of Electroencephalographic recording.

An automated epileptic system, which uses interictal EEG data to categorize the epileptic patients, was devel-

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oped by Forrest Sheng Bao etal. [15].The diagnostic system was used to detect seizure activities for additional examination by doctors and impending patient monitoring. They have built a Probabilistic Neural Network (PNN) fed with four classes of features extracted from the EEG data. Their approach was more efficient when compared to the present conventional seizure detection algorithms because they are seizure independent i.e. doesn't necessitate the seizure activity attained from the EEG recording. This feature shuns intricacy in the EEG collection as interictal data was much easier to be collected than ictal data. In their work, the PNN was employed to classify 38 extracted EEG features. During cross validation their interictal EEG based diagnostic approach achieved a 99.5% overall accuracy. The classification based on ictal data also showed a high (98.3%) degree of accuracy. Thereby, with both interictal and ictal data their algorithm worked well. The function of the classifier was further extended to achieve patient monitoring and focus localization. An accuracy of 77.5% stated impending focus localization. The speed of the classifier was good classifying an EEG segment of 23.6 seconds in just 0.01 seconds.

The efficiency of utilizing an ANN is assessed by Steven Walczak and William J. Nowack [16] in order to determine epileptic seizure occurrences for patients with lateralized bursts of theta (LBT) EEGs. By means of the examination of records of 1,500 successive adult seizure patients training and test cases are obtained. Owing to the development of the ANN categorization models the small resulting pool of 92 patients with LBT EEGs requisite the usage of a jackknife procedure. Evaluations of the ANNs are for accuracy, specificity, and sensitivity on categorization of each patient into the correct two-group categorization: epileptic seizure or non-epileptic seizure. By means of eight variables the original ANN model generated a categorization accuracy of 62%. Consequently, a modified factor analysis, an ANN model using just four of the original variables attained a categorization accuracy of 68%.

Subasi et al [17] compared the traditional method of logistic regression to the more advanced neural network techniques, as mathematical tools for developing classifiers for the detection of epileptic seizure in multi-channel EEG.

Kiymik et al. presented time–frequency analysis of EEG signals for detecting the information on alertness and drowsiness using spectral densities of DWT coefficients as an input to ANN [18]. As compared to the conventional method of frequency analysis using Fourier transform or short time Fourier transform, wavelets enable analysis with a coarse to fine multi-resolution perspective of the signal [19].The detection methods which use the characteristics of the EEG seizure in time or frequency domain are based on the assumption that the segments of the signal are quasi stationary. However recent works shows that the EEG signals exhibit non-stationary behavior. For analyzing such signals, time scale and time frequency methods have proved that the most suitable tools.

Gabor and Seyal [21] introduce a neural network algorithm that relies primarily on the spike field distribution. MLP networks with the number of input and hidden nodes equal to the number of channels in the record and a single output node are used. Five bipolar 8 channel records from the EMU with durations ranging from 7.1 to 23.3 min are used for training and testing. Two networks are trained on only the slopes of the spike's half-waves, and there is no notion of background context. The first uses the slope of the half-wave before the spike's apex for all 8 channels as inputs, and the second uses the slope after the apex. The output of the algorithm is a weighted combination of the two network outputs with a value near 1.0 indicating a spike has been found. The duration (not specified) of the spike half waves is fixed so that no waveform decomposition is required. The algorithm slides along the data one sample at a time and identifies a spike when the output is greater than a threshold (e.g. 0.9). The method requires a distinct network for each patient and spike foci, so 7 networks were trained because two of the patients had independent foci. The training required 4–6 example spikes and the non spikes were generated by statistical variation resulting in 4 times more non-spikes. Although this method does not seem to be well suited for general detection, it might be a promising method for finding 'similar' events.

2.2 Review of Wavelet Transform Based approaches

For the detection of seizure and epilepsy Hojjat Adeli et al. [22] have offered a wavelet chaos methodology for analysis of EEGs and delta, theta, alpha, beta, and gamma sub-bands of EEGs. In the form of the correlation dimension (CD, representing system complexity) and the largest Lyapunov exponent (LLE, representing system chaoticity) the nonlinear dynamics of the original EEGs are quantified. The new wavelet-based methodology isolated the changes in CD and LLE in specific sub-bands of the EEG. The methodology was applied to three diverse groups of EEG signals: healthy subjects, epileptic subjects during a seizure-free interval (interictal EEG), and epileptic subjects during a seizure (ictal EEG).The effectiveness of CD and LLE in distinguishing between the three groups is examined based on statistical importance of the variations. It has been noted that in the values of the parameters acquired from the original EEG there may not be noteworthy differences, differences may be recognized when the parameters were employed in conjunction with particular EEG sub-bands and concluded that for the higher frequency beta and gamma sub-bands, the CD distinguished between the three groups, in disagreement to that the lower frequency alpha sub-band, the LLE distinguished between the three groups.

Subasi [25] deals with a novel method of analysis of EEG signals using discrete wavelet transform, and classification using ANN. In this work the signal decomposed

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in 5 levels using DB4 wavelet filter .The energy of details and approximation were used as the input features.

M.Akin, M.A.Arserim, M.K.Kiymik, I.Turkoglu [26] have tried to find a new solution for diagnosing the epilepsy. For this aim, the Wavelet Transform of the EEG signals have taken, and the δ, θ, α, and β sub frequencies are extracted. Depending on these sub frequencies an artificial neural network has been developed and trained. The accuracy of the neural network outputs is too high (97% for epileptic case, 98% for healthy case, and 93% for pathologic case that have been tested). This means that this neural network identifies the health conditions of the patients approximately as 90 of 100. From this point we can say that an application of this theoretical study will be helpful for the neurologists when they diagnose the epilepsy.

Xiaoli Li [35] proposed an approach based on multi – resolution analysis to automatically indicate the epileptic seizures or other abnormal events in EEG. The energy of EEG signals at the different frequency bands is calculated for detecting the behaviors of brain during epileptic seizures. The energy change of each frequency band is indicated as a feature by calculating the Euclidean distance between a reference segment and the segments extracted in real time. The selection of wavelet functions, scale parameters, width of wavelet function, and sample sizes (segment length) are emphasized. Then, the features go through a recursive in-place growing FIR-median hybrid (RIPG-FMH) filter. The results suggest that wavelet transform is a useful tool to analyze the EEG signals with the epileptic seizures.

Ganesan.M, Sumesh.E.P, Vidhyalavanya.R [36] proposed a technique for the automatic detection of the spikes in long term 18 channel human electroencephalograms (EEG) with less number of data set. The scheme for detecting epileptic and non epileptic spikes in EEG is based on a multi resolution, multi-level analysis and Artificial Neural Network (ANN) approach. The signal on each EEG channel is decomposed into six sub bands using a non-decimated WT. Each sub band is analyzed by using a non-linear energy operator, in order to detect spikes. A parameter extraction stage extracts the parameters of the detected spikes that can be given as the input to ANN classifier. The system is evaluated on testing data from 81 patients, totaling more than 800 hours of recordings.90.0% of the epileptic events were correctly detected and the detection rate of non epileptic events was 98.0%.

2.3 Review of Other approaches

The detection of epileptic seizures from scalp EEG recordings was the area of focus for McSharry et al [23]. A synthetic signal was created by merging a linear random process and a non-linear deterministic process. They introduced a multidimensional probability evolution (MDPE) statistic capable of detecting faint variations in the underlying state space that were associated with modifications in the dynamical equations used in production of synthetic signal.. F-tests were used to calculate the significance of the observed difference between the variances of the recording, all through the learning period and testing the window. Moreover, the significance of the observed difference between the multidimensional distributions observed in the state space all through those periods are attained using tests and also the linear statistics and the MDPE statistics were used by them to analyze the database of scalp EEG recordings. The MDPE and variance were utilized for seizure detection but the MDPE offered better accuracy for seizure onset detection in recordings E/1, E/2, and F/1. Nonlinear statistics largely augmented the scope of automatic detection, but its utilization has justified on a case-by-case basis.

Forrest Sheng Bao et al. [28] have developed a diagnostic system that can employ interictal EEG data to automatically diagnose epilepsy in humans. The system could also detect seizure activities for preceding examination by doctors and impending patient monitoring. The system was developed by extracting three classes of features from the EEG data. These features were fed up with to build a Probabilistic Neural Network (PNN). Leave-one-out cross-validation (LOO-CV) on an extensively used epileptic-normal data set reveals a striking 99.3% accuracy of the system on distinguishing normal people's EEG from patients' interictal EEG. Moreover, it was found that the system can be used in patient monitoring (seizure detection) and seizure focus localization, with 96.7% and 76.5% accuracy respectively on the data set.

G.R. de Bruijne et al. [24] have proposed a patient monitoring system based on audio classification for detecting the epileptic seizures. The system facilitated an automated detection of the epileptic seizures which is likely to have a significant positive impact on the daily care of epilepsy patients. Their system comprised of three stages. First, the signal was improved by means of a microphone array, followed by a noise subtraction procedure. Secondly, the signal was evaluated by audio event detection and audio classification. The characteristics were extracted from the signal on detection of an audio event. Bayesian decision theory was used to categorize the feature vector on the basis of discriminate analysis. At last, it decides whether to activate an alarm or not. With the help of the audio signals obtained from the measurements with the epileptic patients the performance of the system was tested. They have achieved better classification results with a limited set of features.

Sivasankari N and Dr. K. Thanushkodi [27] purposed method for epileptic seizure detection from the recorded EEG brain signals using Fast Independent Component Analysis and ANN. To begin with, independent subcomponents are separated from the recorded signals with the aid of Fast Independent Component Analysis. Further, the signals are trained using ANN (Artificial Neural Networks) technique namely Back propagation algorithm. The exertion of FastICA and ANN proffered encouraging results in the detection of epileptic seizure from the recorded EEG signals. The accuracy results of the proposed approach (76.5% for epileptic case, 66% for healthy case) for the EEG data 200 EEG signals each.

Chua K. C, Chandran V, Rajendra Acharya [31], Lim C. M. proposed nonlinear approach motivated by the higher order spectra (HOS) to differentiate between normal, background (pre-ictal) and epileptic EEG signals. In the work, the features are extracted from the power spectrum and the bispectrum. Their performance is studied by feeding them to a Gaussian mixture model (GMM) classifier. Results show that with selected HOS based features, achieve 93.11% accuracy compared to classification accuracy of 88.78% as that of features derived from power spectral density (PSD).

T. Tzallas, M. G. Tsipouras, and D. I. Fotiadis [32] explored the ability of the Time Frequency analysis to classify EEG segments which contain epileptic seizures. They extracted several time-frequency features and examined the effect of the parameters entering the problem, that is, the frequency resolution of the time-frequency analysis and the number of time windows and frequency sub bands used for feature extraction. Promising results have been reported after the evaluation of the proposed method in four different classification problems, derived from a well-known database. They achieved accuracy of (97.72 – 100%) after testing on different datasets.

Suparerk Janjarasjitt [33] a member of International Journal of Applied Biomedical Engineering proposed method using wavelet transform as a primary computational tool for extracting characteristics of the epileptic EEG signals at various scales (resolutions). The wavelet-based scale variance defined as log-variance of wavelet coefficients of the epileptic EEG signal is used as a feature vector for the classification. The k-means clustering is then used to classify the epileptic EEG data from the corresponding wavelet-based scale variance features. The accuracy for the classification of the epileptic EEG signals for the different set of dataset with variable accuracy from 95.00% - 99.00%

Ralph Meier, Heike Dittrich, Andreas Schulze-Bonhage and Ad Aertsen [34] proposed a method for generic, online, and real-time automatic detection of multi-morphologic ictal-patterns in the human long-term EEG and its validation in continuous, routine clinical EEG recordings from 57 patients with a duration of approximately 43 hours and additional 1,360 hours of seizure-free EEG data for the estimation of the false alarm rates. They Analyzed 91 seizures (37 focal, 54 secondarily generalized) representing the six most common ictal morphologies (alpha, beta, theta, and delta- rhythmic activity, amplitude depression, and polyspikes). And found that taking the seizure morphology into account plays a crucial role in increasing the detection performance of the system. Moreover, besides enabling a reliable (mean false alarm rate < 0.5/h, for specific ictal morphologies < 0.25/h), early and accurate detection (average correct detection rate > 96%) within the first few seconds of ictal patterns in the EEG, this procedure facilitates the automatic categorization of the prevalent seizure morphologies without the necessity to adapt the proposed system to specific patients.

Alexandros T. Tzallas, Markos G. Tsipouras, and Dimitrios I. Fotiadis, members of IEEE [37] proposed method of analysis of EEG signals using time-frequency analysis, and classification using artificial neural network, is introduced. EEG segments are analyzed using a time- frequency distribution and then, several features are extracted for each segment representing the energy distribution over the time frequency plane. The features are used for the training of a neural network. Short-time Fourier transforms and several time-frequency distributions are compared. The proposed approach is tested using a publicly available database and satisfactory results are obtained (89-100% accuracy).

3 Brain Tumor Detection

The brain is an incredibly complex organ. Like a true resident in an Ivory Tower, the brain lives apart from and quite differently than the rest of the body. The brain contains about 10 Billion (10,000,000,000) working brain cells. They are called neurons and make over 13 Trillion (13,000,000,000,000) connections with each other to form the most sophisticated organic computer on the planet -- maybe even the universe. By today's computer standards, the brain far exceeds any network of linked state-of-the-art computers [39]. Although cells in different parts of the body may look and work differently, most repair themselves in the same way, by dividing to make more cells. Normally, this turnover takes place in an orderly and controlled manner. If, for some reason, the process gets out of control, the cells will continue to divide, developing into a lump, which is called a tumor.

Clinical neurologists use Computer Tomography (CT) imaging techniques for diagnosis of brain tumors because of it high accuracy in initial diagnosis of the primary pathology (96% of cases). Such scans stand short, however of analyzing the physiological functioning of the brain as a whole both at the time of initial diagnosis or as part of a long term management of the patient. For such purpose, EEG has been used to render a clearer overall view of the brain functioning at initial diagnosis stages. In brain Tumor diagnostics, EEG is most relevant in assessing how the brain responds to treatments (e.g. post operative)

Being a non-invasive low cost procedure, the EEG is an attractive tumor diagnosis method on its own. It is a reliable tool for the glioma tumor series. The EEG in vascular lesions is abnormal form the onset of symptoms where as a CT only become abnormal on the third or fourth day or after week. The EEG is, however less successful in detecting brain stem tumors and meningioma series.

Murugesan, M. Sukanesh, R [40] proposed a method for automated system for efficient detection of brain tu-

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mors in EEG signals using ANN. The ANN employed in the proposed system is feed forward back propagation neural network. Generally, the EEG signals are bound to contain an assortment of artifacts from both subject and equipment interferences along with essential information regarding abnormalities and brain activity (responses to certain stimuli). Initially, adaptive filtering is applied to remove the artifacts present in the EEG signal. Subsequently, generic features present in the EEG signal are extracted using spectral estimation. Specifically, spectral analysis is achieved by using Fast Fourier Transform that extracts the signal features buried in a wide band of noise. The clean EEG data thus obtained is used as training input to the feed forward back propagation neural network. The trained feed forward back propagation neural network when fed with a test EEG signal, effectively detects the presence of brain tumor in the EEG signal. The experimental results demonstrate the effectiveness of the proposed system in artifacts removal and brain tumor detection.

Seenwasen Chetty, Ganesh K. Venayagamoorthy [41] proposed The ANN based EEG classifier to distinguish between the EEG signal of a normal patient and that of a brain tumor patient. The results show that an artificial neural network is able to distinguish between an abnormal and normal EEG signal, and classify them correctly as brain tumor and healthy patient respectively. This is possible with ANNs since they are able learn the patterns in a normal and abnormal EEG signal. ANN gives a 100% classification success rate with both normal and abnormal EEG.

Fadi N. Karameh, Munther A.Dahleh [42] focused on developing an automated system to identify space occupying lesions on the brain using EEG signals. EEG features are extracted using wavelet transform for different tumor classes and classification by self-organizing maps.

M. Murugesan and Dr. (Mrs.).R. Sukanesh [43] proposed a technique for classification of electroencephalogram (EEG) signals that contain credible cases of brain tumor. The classification technique support vector machine is utilized in the proposed system for detecting brain tumors. The artifacts present in the EEG signal are removed using adaptive filtering. Then the spectral analysis method is applied for extracting generic features embedded in an EEG signal. Precisely, Fast Fourier Transform for spectral analysis is used to separate the signal features which are buried in a wide band of noise. The radial basis function-support vector machine is trained using the clean EEG data obtained. With proper testing and training, they effectively classify the EEG signals with brain tumor.

Rosaria Silipo, Gustavo Deco and Helmut Bartsch [44] proposed a brain tumor classification method on EEG signals. The classification done by applying a nonlinear analysis to the hidden dynamic of the F3 and F4 EEG leads, that describe the electrical activity of the left and right brain hemisphere, respectively. The hidden dynamic of the pair (F3, F4) is tested against a hierarchy of null hypotheses, corresponding to one- and two-dimensional nonlinear Markov models of increasing order. An appreciative measure of information flow, based on higher order cumulates, quantifies the hidden dynamic of each time series and is used as a discriminating statistic for testing the null hypotheses. The minimum order of the accepted Markov models represents a measure of the intrinsic nonlinearity of the underlying system. Rest EEG records of 6 patients with evidence of meningeoma or malignant glioma in lead F4, or without any pathology, are investigated. A high order hidden dynamic is detected in normal EEG records, confirming the very complex structure of the underlying system. Different interdependence degrees between the hidden dynamics of leads (F3, F4) discriminate meningeoma, malignant glioma, and no pathological status, while loss of structure in the hidden dynamic can represent a good hint for glioma / meningeoma localization.

Habl, M. and Bauer, Ch. and Ziegaus, Ch., Lang, Elmar and Schulmeyer, F [45] presented a technique to detect and characterize brain tumors. They removed location arifactual signals, applied a flexible ICA algorithm which does not rely on a priori assumptions about unknown source distribution. They have shown that tumor related EEG signals can be isolated into single independent ICA components. Such signals where not observed in corresponding EEG trace of normal patients.

Lawrence J. Hirsch [46] suggested the use of continuous EEG monitoring (CEEG), which refers to prolonged (hours, days, or weeks) continuously recorded digital EEG in critically ill patients with altered mental status or with a significant risk for acute brain ischemia. Use of CEEG is rapidly expanding, largely due to the widespread availability of digital video/EEG, advances in computer memory storage capabilities, and the ability to review studies remotely via computer networking. He reviewed experience with CEEG in 570 patients who were monitored to detect or rule out Non Convulsive Seizures (NCSzs), or for unexplained decrease in level of consciousness (Claassen et al. 2004). The mean age was 52 years, and 75 patients were younger than 18 years. Overall, seizures were detected in 110 (19%) patients. Importantly, 101 of these 110 patients had exclusively NCSzs; thus, without EEG monitoring, the diagnosis would have been missed. The diagnoses most associated with NCSzs were prior epilepsy (31% had NCSzs), CNS infection (26%), brain tumor (23%), or a recent neurosurgical procedure (23%). Other statistically significant predictors of seizures on CEEG from this population were coma at time of initiation of CEEG (56% of 97 comatose patients had seizures on CEEG), convulsive seizures before monitoring (43% of 134 patients), history of epilepsy (41% of 68 patients), age younger than 18 years (36% of 75 patients), and periodic epileptiform discharges (focal or generalized) on EEG.

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[47] studied 117 patients with verified deep cerebral tumor, qualitatively and statistically in the relation to 60 clinical and EEG variable, s.92 patients had moderate to profound EEG abnormality. They stressed need for adequacy off EEG technique and analyzed factors causing distant rhythms.

4 Conclusion

The EEG signals are commonly utilized to clinically assess brain activities. The detection of epileptic seizures and brain tumor from the EEG signals is a significant process in the diagnosis of epilepsy seizures and brain tumor. More precisely, parameters extracted from EEG signals are greatly valuable for diagnostics. In this paper a lietrature survey of the significant and recent researches that are concerned with effective detection of Epileptic seizures and brain tumor using EEG signals are presented. The main goal behind this review is to assist the researchers in the field of EEG signal analysis to understand the available methods and adopt the same for the detection of neurological disorders associated with EEG.

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